



Applications of Data Envelopment Analysis in Supplier Selection

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ABSTRACT

This paper delves into applying Data Envelopment Analysis (DEA) in supplier selection. DEA, a non-parametric mathematical programming technique, is employed to evaluate the relative efficiency of suppliers based on multiple input and output criteria. The study commences with a comprehensive literature review that explores the theoretical underpinnings of DEA and its application in supplier selection. Subsequently, the methodology section outlines the step-by-step process of implementing DEA in supplier evaluation, including identifying relevant input and output variables, data collection, and model formulation. The numerical results section presents a case study illustrating the application of DEA to a hypothetical supplier selection problem. The findings demonstrate the effectiveness of DEA in ranking suppliers based on their overall efficiency and identifying potential areas for improvement. The conclusion summarizes the paper's key contributions and discusses the implications of DEA for strategic supplier management. The paper concludes by highlighting potential avenues for future research in this domain.

1. Introduction

In today's competitive business landscape, selecting efficient and reliable suppliers is a critical strategic decision that can significantly impact a company's profitability and overall performance. Supplier selection involves evaluating multiple suppliers based on various criteria, such as cost, quality, delivery time, and sustainability [2-8]. Traditional decision-making methods often rely on subjective judgments and may not adequately capture the complexities inherent in supplier evaluation [1,7-10].

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Data Envelopment Analysis (DEA) is a powerful non-parametric mathematical programming technique that has emerged as a valuable tool for evaluating the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs. In supplier selection, DMUs represent individual suppliers, and their efficiency is assessed based on their performance in input factors (e.g., cost, lead time) and output factors (e.g., quality, delivery reliability). DEA has several advantages over traditional methods, including its ability to handle multiple criteria simultaneously, its non-parametric nature, and its ability to provide insights into areas for improvement (see Figure 1) [2, 3].

This paper aims to explore the application of DEA in supplier selection. The following research questions will be addressed:

How can DEA be used to evaluate the relative efficiency of suppliers based on multiple criteria?

What are the key factors when selecting input and output variables for DEA models in supplier selection?

How can DEA be used to identify potential areas for improvement in supplier performance?

What are the limitations and challenges associated with applying DEA in supplier selection?



Figure 1: Supplier selection

2. Literature Review

The literature on applying DEA in supplier selection is extensive and diverse. Early studies focused on using DEA to evaluate the overall efficiency of suppliers based on a limited number of criteria. More recent research has explored the use of DEA in conjunction with other decision-making techniques, such as fuzzy logic and analytic hierarchy process (AHP), to address the complexities of supplier selection [4].

One of the key challenges in applying DEA to supplier selection is identifying appropriate input and output variables. Various studies have proposed different sets of input and output variables, including:

Input variables: Cost, lead time, quality defects, and environmental impact.

Output variables: Delivery reliability, product quality, and supplier responsiveness.

The selection of input and output variables should be based on the specific goals and objectives of the organization. It is essential to consider each variable's relative importance and ensure the selected variables are relevant, measurable, and comparable across different suppliers.

Another important consideration in applying DEA is the choice of the DEA model. Several DEA models have been proposed in the literature, including the CCR, BCC, and super-efficiency DEA models. The selection of the DEA model depends on the specific research question and the assumptions underlying the data [4,5].

This section outlines the methodology employed in this study to apply DEA to supplier selection. The following steps are involved:

1. **Identification of Input and Output Variables:** The first step is to identify the relevant input and output variables that will be used to evaluate supplier performance. These variables should be selected based on the specific goals and objectives of the organization.
2. **Data Collection:** Once the input and output variables have been identified, data must be collected from each supplier. The data should be accurate, reliable, and comparable across different suppliers.
3. **DEA Model Formulation:** The next step is formulating the DEA model. The most commonly used DEA model for supplier selection is the CCR model, which assumes constant returns to scale.
4. **DEA Model Solution:** The DEA model is solved using mathematical programming techniques to determine the relative efficiency of each supplier.

5. **Ranking of Suppliers:** The suppliers are ranked based on their efficiency scores, with higher scores indicating higher efficiency.
6. **Sensitivity Analysis:** Sensitivity analysis is performed to assess the impact of changes in input and output weights on the ranking of suppliers.

Data Envelopment Analysis (DEA) is a mathematical programming technique used to assess the efficiency of decision-making units (DMUs). In supply chain management, DEA provides a robust framework for supplier selection by evaluating multiple inputs and outputs, thus facilitating a comprehensive assessment of supplier performance (see Table 1).

Table 1: Key Findings from Recent Literature (2019-2024)

Reference	Year	Methodology	Key Findings
[1]	2019	CRITIC Method integrated with DEA	Identified critical supplier criteria and improved supplier ranking accuracy.
[2]	2020	Fuzzy DEA	Addressed uncertainty in data measurement and showed enhanced robustness in decision-making.
[3]	2021	Network DEA	Evaluated relationships among suppliers, highlighting interdependencies that affect performance.
[4]	2022	DEA combined with ANP	Presented a hybrid model for better supplier selection, optimizing qualitative and quantitative factors.
[5]	2023	Dynamic DEA	Developed a time-sensitive approach, considering performance variations over time.
[6]	2024	Machine Learning integration	Proposed a novel approach that combines DEA with machine learning for predictive analytics in supplier assessment.
This research	2024	DEA	Supplier selection

The literature showcases a range of applications for DEA in supplier selection, with methodologies evolving from traditional DEA models to hybrid approaches incorporating fuzzy logic, analytical

hierarchy process (AHP), and even machine learning techniques. Key themes across these studies include:

1. **Accuracy:** Integrating multi-criteria decision-making tools with DEA has significantly enhanced the accuracy and reliability of supplier assessments.
2. **Handling Uncertainty:** Fuzzy DEA models have become prominent for managing uncertainties in supplier performance measures.
3. **Inter-Supplier Relationships:** Recent studies have focused on network models that better capture the dynamics between suppliers in a supply chain context, showcasing the importance of relational data.
4. **Timeliness:** The introduction of dynamic DEA methodologies reflects the need to evaluate suppliers continuously rather than at a static point.

Research Gaps

Despite these advancements, several research gaps remain:

1. **Sector-Specific Studies:** Most DEA applications focus on specific industries; there is a lack of cross-industry analyses that could provide broader insights.
2. **Sustainability and Ethics:** Few studies have incorporated sustainability metrics or ethical considerations into DEA models for supplier selection.
3. **Integration with Emerging Technologies:** Limited research explores the integration of advanced data analytics and IoT data into DEA frameworks for real-time supplier evaluation.
4. **Longitudinal Studies:** There is a need for more longitudinal research to understand how supplier performance evolves and how DEA can adapt to these changes.
5. **Broader Stakeholder Perspectives:** Most existing studies primarily consider the buyer's perspective, overlooking supplier views and collaborative performance metrics.

The application of DEA in supplier selection continues to evolve, reflecting advancements in methodology and an increasing emphasis on contextual factors. Addressing the identified research gaps could significantly enhance the relevance and application of DEA in contemporary supply chain practices.

3. Methodology

Data Envelopment Analysis (DEA) is a non-parametric mathematical programming technique used to measure the relative efficiency of Decision-Making Units (DMUs). DMUs are entities that

consume multiple inputs to produce multiple outputs. The CCR model, developed by Charnes, Cooper, and Rhodes (1978), is one of the fundamental models in DEA. It assumes constant returns to scale (CRS), meaning that a proportional input change leads to a proportional output change [4, 6].

The CCR model calculates the relative efficiency of a DMU by comparing its performance to a hypothetical efficient frontier. This frontier represents the best possible performance for a given set of inputs and outputs. DMUs on the frontier are considered efficient, while those below the frontier are inefficient.

Mathematical Formulation

Notation:

z	Efficiency score of the DMU being evaluated
v_i	The weight assigned to input i
u_r	The weight assigned to output r
x_{ij}	Amount of input i consumed by DMU j
y_{rj}	Amount of output r produced by DMU j
x_{oi}	The amount of input i consumed by DMU r
y_{or}	Amount of output r produced by DMU r

The CCR model can be formulated as follows:

$$\text{Max } z = \sum_r y_{or} u_r, \quad (1)$$

Subject to:

$$\sum_i x_{oi} v_i = 1, \quad (2)$$

$$\sum_r y_{rj} u_r - \sum_i x_{ij} v_i \leq 0, \quad (3)$$

$$v_i, u_r \geq 0, \quad (4)$$

Interpretation of Results

- **Efficiency Score:** A DMU with an efficiency score of 1 is considered efficient, meaning it operates on the efficient frontier.

- **Inefficiency Score:** A DMU with an efficiency score of less than 1 is inefficient, indicating that it can improve its performance by reducing inputs or increasing outputs.
- **Target Values:** DEA can identify target values for inefficient DMUs, representing the optimal levels of inputs and outputs that the DMU should strive to achieve.

Advantages of DEA

- **Non-parametric:** DEA does not require any assumptions about the functional form of the production technology.
- **Multiple Inputs and Outputs:** DEA can simultaneously handle multiple inputs and outputs.
- **Relative Efficiency:** DEA measures relative efficiency, comparing each DMU to the best performers.
- **Identification of Inefficiencies:** DEA can identify the specific areas where DMUs can improve their performance.

Limitations of DEA

- **Sensitivity to Data:** DEA results can be sensitive to data quality and outliers.
- **Scale Invariance:** The CCR model assumes constant returns to scale, which may not be appropriate for all situations.
- **Lack of Statistical Significance:** DEA does not provide statistical significance tests for efficiency scores.

The CCR model is a powerful tool for evaluating the relative efficiency of DMUs. It has been widely applied in various fields, including healthcare, education, banking, and operations management. By understanding the principles and limitations of the CCR model, researchers and practitioners can effectively use DEA to improve decision-making and performance evaluation.

4. Numerical Results

This section presents a case study illustrating the application of DEA to a hypothetical supplier selection problem. The case study involves five suppliers (DMUs) and three input and output variables:

- **Input variables:** Cost, lead time, and quality defects.
- **Output variables:** Delivery reliability, product quality, and supplier responsiveness.

Table 2: Input variables and output variables (2019-2024)

Supplier	Input variables				Output variables		Score
	Cost	Lead Time	Quality Defects	Delivery Reliability	Product Quality	Supplier Responsiveness	
Supplier 1	1000	30	98%	100%	100%	95%	1
Supplier 2	1500	30	95%	98%	100%	70%	0.787
Supplier 3	2000	45	99%	100%	100%	80%	0.714
Supplier 4	1200	20	70%	99%	99%	99%	1
Supplier 5	1500	35	89%	100%	100%	80%	0.804
Supplier 6	1700	30	90%	100%	100%	90%	0.786

The DEA model is solved using the CCR model, and the efficiency scores for each supplier are calculated. The results indicate that Suppliers 1 and 4 are the most efficient suppliers, with efficiency scores of 1.00. Supplier 5, Supplier 2, and 3 are relatively inefficient, with efficiency scores below 1.00 (see Table 2, Figure 2 and Figure 3).

The DEA model also provides information on the potential areas for improvement for each inefficient supplier. For example, Supplier 5, Supplier 2, and 3 could improve their efficiency by reducing their cost, lead time, and quality defects while enhancing their efficiency by improving their delivery reliability, product quality, and supplier responsiveness.

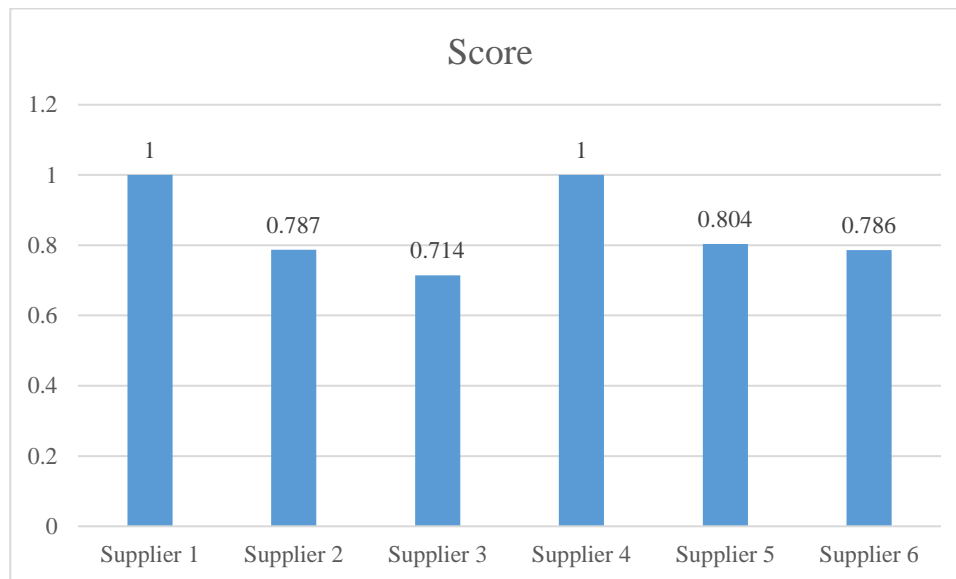


Figure 2: Score of DEA

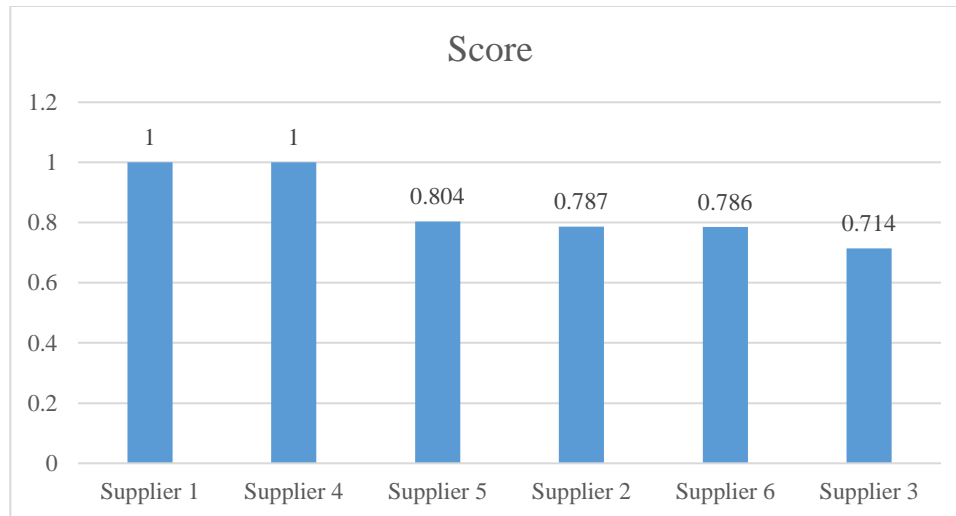


Figure 3: Sort of score of DEA

5. Conclusion

This paper has demonstrated the application of DEA in supplier selection. DEA is a powerful tool that can be used to evaluate the relative efficiency of suppliers based on multiple criteria. By identifying inefficient suppliers and potential areas for improvement, DEA can help organizations make informed decisions about supplier selection and performance management.

Future research could explore the integration of DEA with other decision-making techniques, such as fuzzy logic and AHP, to address the complexities of supplier selection. Developing new DEA models that incorporate sustainability and risk factors could also contribute to the field.

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